**The sky and the stratosphere: wealth
concentration in India during the last (lost)
decade**

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Abstract

This paper provides new and improved estimates of wealth concentration in India over 2012-2018. Official surveys show a decline in wealth inequality and mean wealth per-adult for the first time in three decades. We argue that although these wealth surveys are meant to be nationally representative, they underestimate the upper tail of the Indian wealth distribution – top wealth levels appear orders of magnitudes below externally measured estimates and unrepresentative of increasing stock-market participation over this period. Because wealth is so highly concentrated, wealth in the upper tail matters a lot for realistic estimates of wealth inequality. By combining official surveys and some of the largest datasets of India’s richest persons, we provide new estimates of top wealth shares and total personal wealth in India. We find that personal wealth is underestimated by nearly 54% in official data, and this gap has increased sharply over the 2010s. Our revised estimates show wealth concentration to have sharply increased over 2012-2018. The share of India’s top 1% is higher than similar estimates for Asia, and second only to Russia.

Keywords: Wealth inequality, wealth concentration, Rich lists, Pareto distribution, Top shares, Gini, India, HNWI, surveys

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1 Wealth inequality in India

As confirmed by recent estimates, India is home to the largest number of people (228 million in 2019-21) living in extreme poverty (UNDP and OPHI, 2022). While this figure is not surprising, given that India is still a low-income economy, at the other end, India has also produced numerous billionaires (100-200 in the 2010s) and ultra-rich individuals who constitute the world's wealthiest citizens. Naturally, such social variance indicates very high wealth inequality persists in India. With these facts in mind, in this paper we ask three simple questions: what is the level of wealth inequality in India, has it risen in the last decade, and how does wealth concentration in India compare to other large economies?

In general, economists agree that economic inequality in India is quite high. Mainly, this is confirmed by statistics on income distribution because the official tax authorities publish tabulated income tax returns which can be used to calculate top income shares. Chancel and Piketty (2019) used these data to show Indian income inequality reached historical highs in the 2010s. On the other hand, there is no administrative data generation on wealth and property ownership. Instead, economists and social scientists interested in wealth disparities use a wealth survey¹ published by the official Indian statistical authorities. These surveys have generated four data points, ever since computerized unit level data became available in 1991 (1991, 2002, 2012, 2018), with the most recent version published in 2021 (covering 2018). To be sure, these surveys were developed to gather policy relevant information about credit and debt structures in rural and urban house-

¹For instance, (Anand and Thampi, 2016) show an increase in wealth inequality in India since 1991, using survey data

holds. Since the 1990s, as a cosmopolitan wealthy class has emerged in India, the appropriateness of these surveys to gather information on the “true” richest households has diminished. Besides, wealth surveys in most countries are known to suffer from issues like selective non-response and under-reporting which bias them systematically (Vermeulen, 2018).

To resolve these issues, in this paper we carefully combine the official wealth survey with external data from named rich lists to produce better estimates of top Indian wealth shares for the last decade. Compared to similar² attempts, our advantage is time. Since the early 2000s, as Indians began to mint large private-sector fortunes, several luxury magazines began to compile lists of India’s wealthiest families. An additional demand was created by clients of wealth advisories. Thus, compared to 1991-2012, when these lists had between 1-46 individuals, we use more recent lists compiled by Forbes and Hurun that provide information on hundreds of individuals. Combining these two datasources, we estimate the upper tail of the Indian wealth distribution for 2012 and 2018. Our corrected estimates are, to the best of our knowledge, the most comprehensive estimates of the richest 10 percent of the Indian wealth distribution. Because wealth is highly concentrated, it is imperative to get as close as possible to the “true” upper tail to analyze and compute the concentration and distribution of wealth. In a room of 10 adults, if individuals 1-9 have wealth ranging from Rs 1-9, and the tenth individual is

²For example, Bharti (2018) estimated top wealth shares for India in 1991, 2002 and 2012 using Forbes data. However, the Forbes list in India was (at the time) small and contained between 1-46 observations which did not generate sufficient detail about the shape of the extreme upper tail. The World Inequality Database (wid.world) uses benchmark estimates from Bharti (2018) to extrapolate and interpolate annual wealth inequality series

worth Rs 5000, then it is this last person who matters most for the distribution of wealth. As it turns out, this example is not far from reality.

According to our revised calculations, the official survey underestimates total Indian wealth by nearly 54 percent in 2018, up from 11 percent in 2012. How much do these underestimates matter? The answer is: quite a lot. Based on survey data alone, one would conclude that wealth inequality in India reduced over 2012-18, driven by sharp wealth losses across the top decile. These losses appear to increase as we move further up the distribution. If true, then officially, 2012-18 would represent a complete reversal of wealth inequality between 1991-2018. External evidence sheds doubt on these trends: there were no policies that were implemented in this period which would cause such wealth losses. And, the stock market has expanded relative to GDP. The surveys also show declining stock-market participation over a period where active equity trading accounts in India increased sharply. Most importantly, there is a huge gap – nearly two orders of magnitude in size – between the richest person on the surveys and the poorest persons on named rich lists. In our revised dataset, we estimate wealth shares of the top 10 percent to have increased sharply over 2012-2018, with no evidence of wealth losses. Based on the stratospheric increase in wealth shares of the top 1 percent over this period, our estimates suggest that India has surpassed China, USA and the Asian average in terms of wealth concentration. In 2018, only top Russian wealth shares were higher.

Our main contribution is to provide new estimates of wealth concentration in India and extend it to 2018. As our findings show, the population in the upper tail is orders of magnitude richer than suggested by the survey. Most of the growing

literature on Indian wealth inequality focuses on growing disparities by socio-economic groups (Jayadev et al., 2007; Zacharias and Vakulabharanam, 2011; Bharti, 2018; Tagade et al., 2018), or between rural and urban India (Vakulabharanam and Motiram, 2018). These disparities are important for wealth inequality in the middle class. However, such interpersonal differences are dwarfed by the size of wealth which is concentrated among the rich. Survey data, which is otherwise the benchmark resource for analyzing variation in Indian wealth, misses these magnitudes.

Our findings are also important because they provide distributional insights into a data-scarce decade in India. Since 2011-12, Indian economic statistics have come under scrutiny. Firstly, the former economic advisor to the government claimed that India’s new methodology of GDP estimation flatters actual rates of economic growth (Subramanian, 2019). Secondly, the national statistical authorities did not publish any consumption surveys (used for poverty headcount calculations) – the World Bank itself now uses a private survey to make its poverty calculations. The gist is that over this rather important period in India’s economic development, there are no systematic estimates of inequality. Our wealth estimates are therefore one possible measure of variation in living standards over this period, often referred to as a “lost decade” by economic commentators (Mehra, 2019; Subramanian and Felman, 2022).

2 Wealth inequality in India using survey data alone

We start by enumerating the main results from India’s official wealth survey. The National Statistical Organization (NSO) conducts the All India Debt and Invest-

ment Survey (AIDIS) on a decennial basis. Its primary purpose is a periodic evaluation of the debt and capital expenditure situation of Indian households. The survey itself is nationally representative, containing information on household debt, quantity and value of physical and financial assets such as land, buildings, livestock, transport equipment, agricultural machinery, non-farm business equipment, cash and deposits, bullion and ornaments, mutual funds and shares.

We collected unit-level files from the the 70th (January - December 2013) and 77th (January - December 2019) round³ of the AIDIS. Information on assets and liabilities of households was dated for 30 June 2012 in the 70th round and 30 June 2018 in the 77th round. We combined them with several price series from the Reserve Bank of India's (RBI) database online. Our main deflator is the Consumer Price Index (CPI), calculated separately for rural (CPI-R) and urban (CPI-U) residents. We also use Gold (per 10 grams) and Silver prices (per gram) from transactions on the Mumbai market. Our series on equity prices were collected from the online tool developed by the Federal Reserve of St Louis (FRED). We also used the same source to obtain total stock market capitalization (publicly listed companies only) as a supplementary series. All monetary aggregates were adjusted to 2012 prices using CPI.

³The NSO adopts a stratified two-stage sample design for the surveys. The first-stage units for the surveys are census villages for rural areas and blocks for urban areas. The second stage sampling units for rural and urban areas are households.

Unit-level personal wealth is defined as the monetary sum of all assets⁴, net of liabilities, of each observational unit. That is, for unit i :

$$\text{wealth}_i = \sum \text{non-financial assets}_i + \sum \text{financial assets}_i - \text{debt}_i \quad (1)$$

In our formulation, wealth is defined on a per adult basis, with equal split across all adults in a household. We do not cap the split on spousal basis alone; if a household has 4 adults, then total wealth W will be represented as $W/4$ in our data. We translate sampling weights to account for adults in each households and add up all units with their sampling weights to get aggregate personal wealth, and our control population (total adults) in each year.

We compute both the Gini index and wealth shares for major groups. As is standard, the Gini index ranges between 0 and 1, with 0 representing complete equality (everyone has the same wealth) and 1 representing the extreme upper limit of inequality (one person owns all wealth). Wealth tends to be more concentrated than income; usually, anecdotal estimates of annual fluctuations in the wealth of the richest 100-200 individuals are larger than the stock of wealth of the vast majority. However, the Gini tends to mitigate the effect of such extremes on the distribution. Accordingly, we separately track wealth concentration using top shares. We use wealth shares for every decile (0-10, 10-20 so on) but split the top decile into five subgroups, increasing in wealth: p90-99, p99-p99.9, p99.9-p99.99, p99.99-p99.999 and p99.999-p100 (the Top 0.001 percent). As we will show, changes within the top percentile (p99-p100) are crucial to understanding wealth in India.

⁴We do not include consumer durables in our calculations

2.1 Distribution results from surveys

Year	Class	Share of wealth
2012	Bottom 50%	6.95%
	50-90th percentile	32.90%
	90-99th percentile	34.52%
	Top 1%	25.64%
2018	Bottom 50%	8.89%
	50-90th percentile	38.68%
	90-99th percentile	34.13%
	Top 1%	18.29%

Table 1: Distribution of wealth, 2012 and 2018. Source: Author's calculations from NSO AIDIS surveys.

Our main calculations are shown in Table 1. The official surveys show a clear decline in wealth inequality in India, based on the share of the top 1 percent. In 2012, the richest 1 percent owned around 26 percent of total wealth, but their share reduced to approximately 18% in 2018. On the other end, these reduced shares at the top show up as larger shares of the bottom 90 percent. Using the Gini index, we estimated a steady decline of around 5-6 points with the 2012 Gini estimated at 0.718, against 0.661 in 2018.

This redistributive effect could be driven by faster wealth accumulation at the bottom, wealth losses at the top, or, a combination of both. To capture this effect,

we constructed growth incidence curves (GIC) which measure⁵ the difference in real wealth growth across the distribution between 2012-2018. Figure 1 presents our results. The vertical axis measures per annum growth rates in each decile, percentile or sub-percentile (within the top 1 percent). Our calculations show positive growth for the bottom 90 percent and wealth losses across the top decile, which are especially pronounced⁶ within the top 1 percent and its sub-percentiles.

Our computations also reveal a decline in real wealth per-adult over this period. In 2012, average wealth amounted to Rs 512,832, compared to Rs 457,070 in 2018; a drop of nearly 11 percent over six years. Note that Figure 1 shows real growth in wealth for percentiles 10-90. Therefore, and mostly because wealth distributions are strongly skewed towards the rich, the leveling effect on the top decile ended up reducing average wealth and wealth inequality in India.

2.2 The missing rich?

Although a decline in wealth inequality is plausible, it is unusual for mean wealth to decline in a growing economy. Importantly, the decline in wealth inequality, measured using the Gini⁷, was quantitatively powerful enough to cut the entire

⁵These curves are anonymous, that is, in the absence of longitudinal information on households we are unable to say if the same households occupy a particular ranking in 2012 and 2018.

⁶The sharpest decline occurs in the bottom decile (0-10) – the poorest were further indebted, with a 35 percent negative growth in their average wealth. However, the size of this debt is too small to make any significant difference to the distribution of wealth.

⁷See Appendix A Figure 7 showing comparative time series of the Gini index for wealth from the 1990s to 2018.

Bottom decile (0-10) excluded to preserve scale. (-) 35% growth over 2012-2018

Figure 1: Growth incidence curves calculated from official surveys.

rise in wealth inequality for India since the pro-market reforms of the early 1990s. There are two potential explanations: either the survey is missing the rich, or there were explicitly designed redistributive policies⁸ which successfully reduced wealth concentration. For the latter, this period provides no evidence of fiscal hostility towards the rich. An already defunct wealth tax on top wealth-holders

⁸One possible policy impact might be the 2016 demonetization which rendered high denomination rupee notes (85 percent of total currency) null and void. We note however that cash balances, recorded under financial wealth, was small in comparison to real estate (90 percent of household wealth) and whose share in total wealth actually goes up between 2012-2018. See Appendix A Table 7 where cash is subsumed under Other Financial Balances.

was eliminated in 2015 and there was no tightening of the income tax code. But there is plenty of reason to believe that the AIDIS is unable to account for India's actual rich.

Wealth surveys worldwide are known to have problems capturing the actual rich (Davies and Shorrocks, 2000). Common issues include sampling error, systematic nonresponse correlated with wealth and underreporting of assets (or debt). Because wealth is highly concentrated – a few persons might be worth 1000 times the wealth of typical individuals in the upper class but their probability of selection is low – sampling errors are unavoidable in surveys which do not oversample the rich⁹ with administrative data; the SCF in US, for example, oversamples and gets close to estimates of top wealth shares using alternate methods (Bricker et al., 2016). The AIDIS does not follow oversampling at the top. Unsurprisingly, in 2018, Forbes estimated the wealth of India's 100th richest person to be Rs 69 billion, while the survey reported the richest Indian to be worth Rs 244 million. In fact, Forbes data also shows much larger wealth magnitudes¹⁰ than plausible in the AIDIS.

While such issues are universal to wealth surveys, the 2018 AIDIS also appears to have especially¹¹ glaring anomalies. For instance, Mumbai is India's financial

⁹Vermeulen (2018) shows top wealth share estimates to depart from survey estimates by a bigger margin when the survey in use does not oversample the rich.

¹⁰Jayaraj and Subramanian (2018) find that the wealth of the top 100 richest families in India was equivalent to nearly one-fifth of India's GDP in 2017.

¹¹Private conversations with anonymous NSO employees suggest the survey infrastructure has been underfunded in the last decade.

Figure 2: Index prices of equities, gold and silver. Source: Federal Reserve of St Louis (FRED) and Reserve Bank of India

capital and home to many billionaires and multi-millionaires, followed by other cosmopolitan cities like Delhi and Bangalore. However, the 2018 AIDIS reports the wealthiest Indians to be located in the state of Rajasthan and Meghalaya – relatively poorer states. In addition, financial wealth does not tally with trends observed in external data. The fraction of households who hold equities declined from 3.6 to 1.4 percent over 2012-2018. During the same period, the Securities and Exchange Board of India shows a near doubling in stock-market trading

accounts (20 to 35 million). A decomposition of wealth by percentile¹² shows equities to only comprise 0.1 percent of the net wealth of the top 1 percent, which is highly unusual considering that most billionaires are wealthy due to their shares of listed companies. Finally, in contrast to the decline in upper class wealth, and growth of middle class wealth shown in Figure 1, a comparison of asset prices in Figure 2 shows real equity prices grew faster than precious metals. The latter tend to be mostly concentrated in the middle class and the former among the rich.

In sum, there is a strong case in favor of these surveys underestimating India's upper class. Consequentially, they also miss an increasingly important source of Indian wealth (financial wealth in capital markets), thereby suggesting lower estimates of household wealth than would be found in (say) a hypothetical census of assets and debt in accordance with national accounting norms. In a hypothetical scenario, a comparison of survey wealth totals against household wealth on national account balance sheets would provide confirmation but such accounts are not published by India's official statistical authorities.

3 Introducing the super-rich to the vast majority

To correct the downward bias in the upper tail, we introduce data from named rich-lists, published by luxury magazines. Recently, the use of these lists, as a supplementary source with wealth surveys, has proliferated in the literature; including for non-OECD countries. For instance, Novokmet et al. (2018) used rich lists to supplement survey data for Russia, Piketty et al. (2019) for China and Bach et al.

¹²See Appendix A Table 7

(2019) for France, Germany and Spain. Economists and social scientists have also studied named rich-lists as an exclusive source of information about India's wealthiest. Sinha (2006) used rich-lists published by Business Standard magazine in 2002-04 to show evidence for power-laws in the upper tail. Gandhi and Walton (2012) analyzed Forbes lists to decipher the source of wealth. However, until recently, there were very few observations on Forbes' India lists. In 1991-92, the list was a single individual, which grew to 46 billionaires by 2012. Bharti (2018) simulated a Pareto tail backwards from these observations to replace the top 5 percent in the AIDIS survey for 1991, 2002 and 2012.

Since 2012, Forbes has expanded its "India's richest" publications. Their new lists are an annual ranking of the 100 richest Indians, which are aggressively marketed with other lists of top-earners in professions like entertainment and sports. As per-capita GDP and professional incomes have grown in India over the last few decades, so has the appetite for consuming this type of information. Several new players have entered the market¹³ to satiate this demand; the most prominent of these is the Hurun, whose lists are published in collaboration with Barclays bank.

To correct the upper tail on the survey, we add information on India's wealthiest from both Forbes and Hurun-Barclays. While Forbes is the traditional go-to source for such exercises, Hurun-Barclays¹⁴ (Hurun henceforth) has begun to

¹³Several investment advisories also maintain their own lists and estimates of high net worth individuals in India as a service to their clients. However, these lists are not available on the public domain.

¹⁴Piketty et al. (2019) also use Hurun as their supplementary information to correct Chinese wealth surveys for top wealth shares.

maintain larger lists which number in the hundreds. We scraped both websites to obtain computer-friendly lists of India's wealthiest persons for 2012-2018. While we have 100 annual observations in the Forbes list, we have over 800 observations on the Hurun list. Thereafter, we converted monetary amounts of each observation to Indian Rupees using annually averaged exchange rates and adjusted them for inflation using CPI.

3.1 Caveats on rich-list data

In continuing with our correction strategy, we are assuming that rich-list data are reasonably accurate. Obviously, this is subject to interpretation. The methodology for arriving at these wealth estimates of ultra-high net worth individuals and families is not fully transparent. According to online sources, the journalists who compile these lists combine information obtained from family interviews and regulatory agencies. Shareholding is valued using publicly available prices for public companies, and similar companies for privately held businesses. For instance, Figure 3 shows the mean wealth of India's 100 richest persons, along with the ratio of stock-market capitalization to GDP. They correlate well. Therefore, rich-lists might be reasonably reliable at tracking the wealthiest, based on their stakes in listed companies, or even if prices of unlisted companies follow stock-market indices.

The caveats to reliably measuring the wealth of visible individuals are well known in the literature (Davies and Shorrocks, 2000; Atkinson, 2006; Raub et al.,

Figure 3: Average wealth (Rs billions in 2012 prices) of India’s 100 richest and stock-market capitalization to GDP (in percent).

2010); these include the valuation of prestigious works of art¹⁵, visibility of assets versus debt, citizenship¹⁶ etc. Since the survey downplays financial wealth quite clearly, and rich-lists overplay them, both datasets are biased towards specific classes of assets. Our estimates should be understood with these limitations; they

¹⁵In the last decade, Hurun has begun tracking the value and sale of works of art, possibly as a response to such issues, or as additional service to clients.

¹⁶According to both Hurun and Forbes, a few individuals on their Indian lists may be foreign citizens but who also hold significant business ties to the country.

are still far from an ideal measure, such as a census of assets and liabilities. For our purposes, adding this information recalibrates the scale for wealth ownership amongst rich Indians, therefore serving as a supplementary source to mitigate downward bias in surveys. These data limitations would bear heavily were we to use them as the sole datasource to replace the tail from surveys (we pool both datasources). In anticipation of expected changes, we confirmed (Appendix A, Figure 8) that even adding the rich-list on top of the survey reverses the growth incidence curve – from negative to positive growth rates – at the absolute top (richest 0.001 percent).

3.2 Methodology to replace the survey upper tail

Our correction strategy follows the methodology shown in Vermeulen (2018). We introduce the Pareto distribution $P_{W>w} \propto w^{-a}$ which gives the probability P of observing wealth larger than w . The parameter a is the Pareto coefficient which determines the thickness of the tail – tails are thicker (greater inequality) when a is small. It is well known that wealth distributions follow these power-law type probability distributions ever since Vilfredo Pareto originally discovered them in European data. To recompute a corrected tail, we (a) select an appropriate wealth cutoff for Pareto replacement on the survey, (b) estimate parameters of the Pareto distribution by pooling the rich-list with survey data above the cutoff, and (c) use these parameters to replace the distribution above the cutoff on the survey.

The official survey is a sample with weights, thus not suited to the best-fit methodology of identifying Pareto cutoffs in random samples (Clauset et al., 2009). Accordingly, picking an appropriate cutoff is a matter of researcher judge-

ment. We tested thresholds of Rs 1 million (larger sample), Rs 5 million (small sample) on the survey using the power-law regression specification in log-log form:

$$\log rank_i = \beta - a \log w_i \quad (2)$$

Our regressions showed (Appendix A, Table 8) that the larger sample, at Rs 1 million, obeys the power-law relationship very well. The same power-law cutoff is also confirmed in income distribution data (which has good coverage of the upper tail) for 2012-13 by Kumar (2017). We also verified¹⁷ this cutoff to hold consistently, with excellent fits to the Pareto distribution, using income tax tabulations for 2012-2018. Thus, we choose Rs 1 million as our 2012 cutoff¹⁸ for the Pareto class in our adjustment. This selects just fractionally below the top ten percent. Using growth rates of mean wealth, we arrived at cutoffs for the top 10 percent in 2018.

To estimate the parameters of the Pareto distribution, we pooled the survey, keeping observations above the chosen thresholds, with rich-list data. We use Hu-

¹⁷For details see Appendix A Figure 9.

¹⁸As discussed previously, the downward bias in the 2018 survey appears to have grown thus leading to thin tails. We estimated unusually large Pareto coefficients ($a \approx 2$) in our regressions when we moved the cutoff to Rs 5 million; higher than the estimate for Rs 1 million. In the literature, Pareto coefficients for wealth hover between 1.2-1.6. For supplementary verification, the cutoff estimated using the Clauset et al. (2009) methodology (but without sampling weights) was found to be intermediate to our two proposed thresholds.

run in our benchmark dataset, because of its much larger sample¹⁹ sample size. Before proceeding with regressions, we modify Eqn 2 to recover unbiased estimates: $\log(rank_i)$ is converted to $\log(rank_i - 1/2)$ in order to reduce leading order bias (Gabaix and Ibragimov, 2011). Then, following the weighting strategy for pooled survey and billionaire data in Vermeulen (2018), we assign rich-list observations with a weight of 1 if individuals, and 2 if multiple family members are listed (wealth is divided accordingly). The dataset is sorted in descending order, by year and for each observation we calculate $\bar{S}_i/S_m$. Here, $\bar{S}_i$ is the *mean weight of the first i observations*, and S_m is the mean sample weight. Our modified regression takes the form:

$$\log((rank_i - 1/2) \frac{\bar{S}_i}{S_m}) = \beta - a \log w_i \quad (3)$$

Our estimation results are shown in Table 2. Firstly, note that all estimated coefficients are highly significant and produce excellent fits to the power-law relationship (Eqn 3). More importantly, we note that the absolute value of the Pareto coefficient is lower relative to the survey data alone, and declines over 2012-2018 – thus reversing of our findings from survey data²⁰ alone. Thus, the upper tail thickens in time (wealth concentration above the cutoff increased in 2018). Using these parameters, we recalculate average and total wealth assuming a Pareto distribution for the top 10-0.001 percent, and a revised wealth distribution for In-

¹⁹Bach et al. (2019) show that a larger rich-list improves the estimation of the Pareto coefficient when pooling with surveys. Forbes list only rank India’s 100 richest. As a robustness check, we tested the top 100 on both lists in Appendix A Table 9 using rank-size regressions (Eqn 2) and found good proximity between their estimated coefficients (β , a).

²⁰See Appendix A Figure 9 for regression tables on survey data alone

	(1)	(2)
	2012	2018
Dependent variable: adjusted rank (log)		
Log wealth	-1.37*** (0.00)	-1.28*** (0.00)
Constant	28.25*** (0.02)	26.90*** (0.02)
Observations	13658	16377
Adjusted R-squared	0.987	0.987
Standard errors in parentheses		
Pooled data (Survey and Rich-Lists)		
* p<0.10 ** p<0.05 *** p<0.01		

Table 2: Estimated Pareto coefficients for pooled survey and rich-list data. Adjustments to rank follow Gabaix and Ibragimov (2011) and relative weights follow Vermeulen (2018)

dia in both years. All our procedures are reproduced in the supplementary excel worksheet.

4 New estimates of wealth concentration in India

By modifying the tail with two sources of data and estimated parameters of the Pareto distribution, we have changed not just the distribution, but also the magnitude of total personal wealth in 2012 and 2018. That is, beyond the threshold

point w^* in each year, we replace total wealth with $\int_{w^*}^{\infty} w \cdot p'(w) dw$ where $p'(w)$ is the probability density of the Pareto distribution. Naturally, all this “replaced” wealth is allocated to the upper tail, thereby raising their share of personal wealth, relative to the survey. To start with, we show the change in aggregate personal wealth in both years. These results were already pre-empted in Table 2 by the thickening of the upper tail using our fitted power-law lines. Table 3 shows the magnitude of increase in personal wealth from our adjustments. Our estimates increase personal wealth by 11 percent in 2012, and a staggering 54 percent in 2018. As per our calculations, real wealth with adjusted tails grew at 5.5 percent per annum between 2012-2018, still short of 7.7 percent per annum GDP growth over the same period. We do not pretend to have “recovered” 100 percent of wealth missed on the survey – there may be misreported wealth in the bottom 90 percent, and more to be found in the top 10 percent – but clearly, the impact of the revising wealth by these margins is big.

Household wealth in India, CPI adjusted. Rs Billions

	Official (1)	Our estimate (2)	Increase in wealth (2/1)
2012	349,733.91	389,023.22	111%
2018	349,927.02	537,483.49	154%

Table 3: Total household wealth in India: surveys versus revisions. Sources: Author’s calculations using NSO surveys and named rich list data.

Our main distribution results are shown in Table 4. As expected, wealth shares of the top 1 percent go up across datasets. But, more significantly, the revised

wealth of the upper tail is large enough that it fully reverses the survey’s findings of declining wealth inequality. Our estimates show that the top 1 percent’s wealth shares actually increased, from around 35 percent to 42 percent between 2012 and 2018. In essence, these results are driven by our hypothesis of the surveys missing most of the wealth in the upper tail, which was already quite concentrated. Once we allocated a larger magnitude to the top decile, the parameters of the power-law attracted most of this added wealth into the top 1 percent. To be sure, such a large increase at the top has to be “made up” by reducing the shares of lower groups. Mainly, we observe much smaller shares of the middle class (50-90th percentile) and also a reduction in the 90-99th percentiles. The main beneficiaries (in terms of wealth shares) of our adjustments are, therefore, India’s wealthiest 1 percent.

Shares of main population fractions

Year	Class	Share of wealth (s)	Share of wealth (c)
2012	Bottom 50%	6.95%	6.24%
	50-90th percentile	32.90%	29.57%
	90-99th percentile	34.52%	29.33%
	Top 1%	25.64%	34.85%
2018	Bottom 50%	8.89%	5.79%
	50-90th percentile	38.68%	25.18%
	90-99th percentile	34.13%	27.15%
	Top 1%	18.29%	41.88%

Table 4: Distribution of wealth, 2012 and 2018: surveys (s) versus corrections (c).

Source: Author’s calculations from NSO AIDIS surveys and named rich lists

Our methodology also produces a different outcome to similar studies for other countries. In countries like Italy and Netherlands, where surveys do not oversample the rich, Pareto correction tends to make level changes to the wealth share (Vermeulen, 2016). In our case, both level and trend are changed because we replace thinning tails (surveys) with fattening tails over time. Fractal properties of Pareto distributions do the rest. That is, not only is the magnitude of wealth larger for the upper tail, but its distribution is more skewed within the upper tail itself. For instance, Figure 4 compares growth incidence curves²¹ produced by the survey and our corrections. Each point on the curve shows CPI adjusted wealth growth between 2012-2018 for the relevant fraction of society. As alluded to previously, our revised estimates reverse the trend in the survey. Mean wealth (real) for each fraction of society grows faster as we move further up the upper tail. Accordingly, the richer the percentile, the larger the gap between the survey and our corrected estimate. For instance, our results suggest that wealth grew faster over 2012-2018 for the entire top 10 percent compared to any other decile in the survey. At the top 0.001 percent, the rate of growth is just short of the growth of wealth conveyed by rich lists.

The difference in wealth growth within the top decile is important for distributional purposes. Note that the top decile's wealth will be higher due to our adjustments anyway. However, the fact that we fit a fatter tail in 2018 (relative to 2012) also concentrates more wealth within the top decile. Table 5 shows wealth shares for intermediate groups in the top decile. We observe a reduction in wealth

²¹Note, in this GIC, we cumulate the population above the top 10 percent progressively. In Figure 1, we were using mutually exclusive fractions of the upper tail.

Figure 4: Growth incidence curves calculated from official surveys and corrections

shares for the 90-99th percentile, basically due to higher shares allocated above the 99.9th percentile.

4.1 Comparison with other estimates and countries

Next, we place our findings in a slightly longer context by comparing our estimates with trends in wealth inequality in India since 1990. In Figure 5, our results (including the survey) are laid side-by-side with other estimates in the literature. Our findings show wealth inequality – measured by the wealth share of the top 1

Shares of intermediate fractiles

Year	Fractiles	Share of wealth (s)	Share of wealth (c)
2012	p90-99	34.52%	29.33%
	p99-99.9	13.60%	16.14%
	p99.9-99.99	7.10%	8.67%
	p99.99-99.999	4.22%	4.65%
2018	p90-99	34.13%	27.15%
	p99-99.9	12.85%	16.57%
	p99.9-99.99	3.76%	10.01%
	p99.99-99.999	1.34%	6.05%

Table 5: Share of wealth: intermediate groups in top decile, surveys (s) and corrections (c). Source: Author’s calculations from NSO AIDIS surveys and named rich lists

percent – to be much higher than all other estimates. For instance, compared to the pure survey based estimates in Anand and Thampi (2016), our level is much higher²² because of Pareto correction. Interestingly, our estimates are also higher in level, and increasing in trend, compared to the WID (equal-split) estimate which is mostly stable in time after 2012. The latter is based on Bharti (2018) and extrapolated to 2021 using covariates from benchmark shares estimated in 2012. In addition, Bharti (2018) extrapolates backwards from 46 rich-list observations (using power-law rank-size relationships), adjusting roughly the top 5 percent of the

²²Note that our survey based estimate is lower than Anand and Thampi (2016) for 2012. The reason is our use of wealth per-adult, whereas Anand and Thampi (2016) calculate wealth per-capita.

survey distribution. By comparison, our adjustment applies to double the population. The fractal properties of the power law thereafter allocate larger shares to the top 1 percent in our dataset. In sum, our estimates imply that personal wealth is chronically underestimated in India and its concentration was probably higher in 2018 than at any other point in the previous three decades.

Figure 5: Wealth concentration in India according to different estimates.

Next, we compare wealth inequality in India against other countries and world regions; all our data, excluding India, were downloaded from WID. For most countries, WID uses a combination of survey and rich-list data, thus making our estimates quite comparable in method. In Figure 6 we compare the Indian top 1

percent to their counterparts in China, Russia, US as well as WID’s estimate of top shares for Asia and the entire world. In 2012, wealth concentration in India tallied almost exactly with top shares predicted for Asia, and slightly below the estimate for the entire planet. By 2018, India was the most wealth unequal region in Asia, also by then exceeding WID’s estimate for the world. Our data basically confirms the “Gilded age” narrative of India in the 2010s described in Crabtree (2019) and perhaps it is appropriate that India’s rich are closest in wealth shares to Russia, where oligarchic elites exercise disproportionate control of wealth through strategic sectors (Novokmet et al., 2018).

Figure 6: Top 1 percent wealth shares: India and other regions.

Average wealth (2018), % of US (per-adult)

	Survey	Our corrections
Bottom 50 percent	0.5%	0.5%
50-90th percentile	2.6%	2.6%
90-99th percentile	10.3%	12.6%
Top 1%	38.9%	175.5%
Top 0.1%	114.1%	1060.6%
Top 0.01%	407.7%	6409.5%
Top 0.001%	926.3%	38732.1%
Richest 100	1093501.4%	

Table 6: Indian wealth distribution, normalized to US per-adult wealth. US per-adult wealth collected from World Inequality Database.

To conclude our results, we ask a simple question: how do we best summarize the degree of wealth inequality and affluence in a comparative setting? To illustrate, we normalize average wealth across the distribution in 2018 to the per-adult wealth of a rich country – we use the US in our example. Basically, while we expect most Indians to be poor given the tenfold per-capita income difference between both countries, we should be able to see a smooth transition to the upper class which has much higher wealth than estimated on survey data alone. This comparison should extend below the richest 100 and reflect astronomical real estate prices in top cities, and the fact that hundreds of thousands of Indian students regularly pay tuition for undergraduate education in rich countries like the US and

UK. Table 6 shows our results. Interestingly, only Indians in the top percentile possess more wealth than the average American. In fact, the 90-99th percentile are only worth 12-14 percent US wealth per-adult. The top percentile is where Indian wealth begins to approximate US standards, something simply not captured by the survey-based estimates. India's super-rich (top 0.1 percent onwards), roughly 700,000 adults, are ten times as wealthy as the average American which puts them close to the top percentile of the US wealth distribution. This brings us back to the point made at the beginning of this paper, which we now back with quantitative estimates. While most Indians are very poor, India's richest are wealthier than most citizens of the world's wealthiest country.

5 Discussion and conclusion

In this paper, we showed that the official surveys conducted by India's official statistical agencies fall short of capturing a very large amount of household wealth, and, the gap to more plausible levels has grown over 2012-2018. Once we adjusted the top of the distribution, we found wealth concentration in India to have soared to stratospheric levels in the last decade, higher than perhaps anytime since this trend started in the early 1990s. Of note is the fact that our corrections not only improve these estimates but reverse the findings in official statistics. Often in discussions, India's reduction of poverty is cited as a success of its adopted economic paradigm and impressive economic growth rates. Clearly, the impact of growth in reducing poverty may have been overshadowed by the rate at which wealth has continually become concentrated. We should emphasize that these estimates are certainly not definitive, but our methods are backed by similar strategies adopted

by others in the literature.

Our results also suggest that a lot can be done by the official statistical agencies in India to improve their data-generation processes. Given the rise of wealth in the upper class, supplementing these surveys with oversampling strategies is both warranted and feasible; income tax returns generate sufficient geographic information on the rich. As per-capita incomes grow, differences in wealth might become important not just for assessment of debt situations in rural India, but also to evaluate equality of opportunity which is itself mitigated by sharp variation in, and intergenerational transmission of, wealth. New policy frontiers therefore require a more up-to-date survey process. At the very least, it is high time for the central bank's researchers to publish household balance sheets on a more regular basis using methods outlined in the UN system of national accounts. Such initiatives will improve our understanding of Indian wealth.

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Appendices

A Supplementary figures and tables

Year	Group	Real Estate	Production capital	Equity	Other Fin	Metals	Debt
2012	0-50	89.8	8.5	0.0	5.2	11.8	-15.5
	50-80	88.9	5.2	0.0	3.8	6.2	-4.1
	80-95	91.6	4.1	0.1	3.8	3.8	-3.3
	95-99	92.7	3.3	0.2	3.5	2.6	-2.2
	99-100	96.2	1.8	0.2	1.8	1.0	-1.0
	Overall	92.4	3.8	0.1	3.3	3.8	-3.5
2018	0-50	89.1	8.1	0.0	9.3	9.5	-15.9
	50-80	87.7	4.6	0.0	7.7	4.5	-4.5
	80-95	90.7	3.7	0.0	6.2	2.7	-3.3
	95-99	91.2	3.2	0.1	6.3	1.7	-2.4
	99-100	91.8	2.4	0.2	5.8	0.8	-1.1
	Overall	90.2	3.9	0.1	6.8	3.1	-4.1

Table 7: Composition of wealth by wealth ranking. Rows sum to 100 percent.

Reading: *In 2018, the bottom 50 percent of the adult population (ranked by net wealth) held 89 percent of its wealth in the form of real estate (land and buildings)*

Figure 7: Gini index for wealth, 1990s to present. Our computation on surveys on per-adult basis, Anand and Thampi (2016) computed on per-capita basis, WID (Bharti, 2018) computed using equal-split adults.

Bottom decile (0-10) excluded to preserve scale. Negative wealth (2012, 2018) & growth rate

Figure 8: Growth incidence curves calculated from survey data with richest Indians appended on dataset. Assumes rich-list observations have sampling weight equal to no. of adults. The upper tail has not been replaced. We simply extend the tail of the survey with a few hundred observations from journalistic rich-lists and assign to the rich a weight equal to the number of adults indicated on the rich-list (explained shortly) so that each rich-list observation only represents themselves. The total population thus expands by the number of new adult observations.

Figure 9: Fraction of taxpayers above Rs 1 million cutoff, 2012-2018. Source: Annual tax return tabulations on website of Income Tax Department, Government of India. The Indian income tax authorities publish tabulations showing tax-returns as a function of an income bracket $[y_{min}, y_{max}]$. These are administrative data which we downloaded from the website of the income tax department. Short of under-reporting income to tax authorities, they do not suffer from the middle class biases of surveys. We cumulated returns filed above Rs 1 million sequentially using y_{min} as a threshold, and normalized them to the total number of tax returns. $P_{Y>y} \propto y^{-a}$ implies a linear decay in $P_{Y>y}$ against y on a log-log scale which was confirmed visually and with OLS regression of $P_{Y>y}$ on y .

	Clauset et al, 2009		Rs 1 million threshold		Rs 5 million threshold	
	(1)	(2)	(1)	(2)	(1)	(2)
	2012	2018	2012	2018	2012	2018
Log wealth	-1.66*** (0.00)	-1.86*** (0.00)	-1.57*** (0.00)	-1.76*** (0.00)	-1.56*** (0.01)	-1.98*** (0.01)
Constant	32.61*** (0.04)	35.24*** (0.05)	31.10*** (0.01)	33.84*** (0.01)	30.98*** (0.10)	37.25*** (0.15)
Observations	3608	3659	13558	15546	1332	1128
Adjusted R-squared	0.991	0.988	0.994	0.996	0.980	0.976

Standard errors in parentheses

Survey data adjusted weights

* p<0.10 ** p<0.05 *** p<0.01

Table 8: Regression results, survey data only. Dependent variable is log (adjusted rank). Adjustments follow Gabaix and Ibragimov (2011) to rank and Vermeulen (2018) to compute relative weights.

	(1)	(2)
	Forbes100	Hurun100
Log wealth	-1.25*** (0.03)	-1.28*** (0.03)
Constant	35.73*** (0.72)	36.22*** (0.66)
Observations	100	100
Adjusted R-squared	0.953	0.961

Standard errors in parentheses

2018 Forbes and Hurun Top 100

* $p < 0.10$

** $p < 0.05$

*** $p < 0.01$

Table 9: Rank-size regressions (log-log) on Top 100 richest units in Forbes and Hurun (2018). Uses adjusted rank specification for small sample power-law estimation, following Gabaix and Ibragimov (2011).